

RESEARCH

Artificial Intelligence and Human Cognitive Bias in Industry 4.0: The Need for Sustainable Skills Development

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ABSTRACT

PURPOSE: The study aims to explore the impact of Artificial Intelligence (AI) and human cognitive bias on sustainable skill development in Industry 4.0.

DESIGN/METHODOLOGY: A secondary data analysis is conducted using the Kaggle AI Impact on Job Sector (2026) dataset and the United Nations Educational, Scientific and Cultural Organisation (UNESCO) Science Report (2021). Microsoft Excel is used to perform comparative, pattern, and sectoral workforce analyses.

FINDINGS: The data show that even as more organisations adopt AI, disparities persist in workforce participation, representation in leadership positions, and compensation equality. Additional productivity gains are not always accompanied by comparable reward opportunities and continue to vary across sectors and AI-focused career trajectories due to cognitive biases.

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ORIGINALITY/VALUE: The study shifts the focus from whether AI is biased to whether AI-driven organisations provide equitable opportunities to participate, advance, and be recognised. Cognitive Bias Theory (CBT) is used as a novel interpretive theory to explain how organisational asymmetries may persist within data-driven environments.

RESEARCH LIMITATIONS: The study is based on secondary and exploratory data and does not directly measure cognitive bias.

PRACTICAL IMPLICATIONS: Skills development for sustainable Industry 5.0 requires not just technology but also workforce governance mechanisms that enable and empower inclusive workforce participation, and sustain progression and incentives.

KEYWORDS: *Cognitive Bias; Sustainable Skills Development; Cognitive Bias Theory; Workforce Transformation; Artificial Intelligence Impact; Organisational Asymmetries; Industry 4.0.*

INTRODUCTION

Industry 4.0 has transformed organisational systems with the advent of Artificial Intelligence (AI), automation, advanced analytics, and digital technologies. These advancements have not only helped increase productivity and speed digital transformation but also driven the need for continuous skills development, workforce agility, and organisational resilience (Sony and Naik, 2020). Hence, sustainable organisational development is increasingly a matter of the capacity to build inclusive workforce systems that can sustain long-term participation in emerging digital economies, as well as technological progress. While there have been major investments in AI-powered workforce systems, organisations still struggle with a shortage of technical talent, a lack of leadership diversity, workforce participation, and employee retention. Studies have indicated that AI applications have the potential to enhance decision-making efficiency and staff management, but historical workforce structures and decision-making processes in the organisation/agency can affect the way technological systems are used (Tambe *et al.*, 2019; Chen, 2023). This means that better technological capacities do not always translate into better inclusion of the workforce or achieve equitable access to development opportunities.

Sustainable Skills Development focuses on the ongoing development, application and acknowledgement of AI skills and capabilities within the workforce for organisational resilience (Siddamal *et al.*, 2020; Sony and Naik, 2020). In this context, sustainable workforce development is not just about technical training; it encompasses access to participation and leadership opportunities, and recognition systems in human resource settings (Podgorodnichenko *et al.*, 2020). Unless these opportunities are

evenly distributed across genders, a persistent gap between organisations' technological transformation and workforce sustainability will persist.

Although the uptake of AI and algorithmic bias, along with workforce inequality, is researched extensively, there are very few studies on how AI is enabling more sustainable skills development across several layers of the organisational landscape. However, connecting technological shifts to workforce resilience, innovation capacity, and long-term sustainability goals is critical. Within organisational settings, cognitive bias is relevant not only as an individual behavioural phenomenon but as a possible mechanism for participation, progression, and valuation in the labour force. The study seeks to address the shift by integrating the United Nations Educational, Scientific and Cultural Organisation (UNESCO) Science Report (UNESCO, 2021) with the organisational AI adoption dataset from the Kaggle AI Impact on Job Sector dataset (Kaggle, 2026). It investigates how AI-based workforce systems are promoting sustainable skills development and understands whether structural imbalances remain key factors determining the outcomes of work activities in the context of Industry 4.0.

The study is guided by the following research questions (RQ):

RQ1: How do organisational asymmetries and cognitive bias influence workforce participation in AI-oriented workforce systems and sustainable skills development in Industry 4.0?

RQ2: To what extent do AI-enabled organisational systems contribute to workforce productivity while supporting inclusive and sustainable organisational development?

Contribution of the Study

The study's originality lies in exploring how AI can be made more inclusive to foster sustainable skill development in organisations, despite existing biases. It applies Cognitive Bias Theory (CBT) in interpreting workforce asymmetries using the Kaggle dataset, leadership disparities, and productivity-reward misalignment using the UNESCO Report within AI-enabled organisational systems. The study offers a new perspective on persistent organisational inequalities despite technological sophistication and connects workforce inclusion as a precondition for sustainable skills development in Industry 4.0.

Theoretical Background

According to Tversky and Kahneman (1974), cognitive bias is an unconscious pattern that occurs when the human brain does not make judgements in accordance with

objective reality. Organisationally, it means that fair judgements are not always fact-based, but rather assumptions, shortcuts (heuristics), and psychologically internalised assessments of competencies that shape perceptions of leadership potential and the value of employees. These biases can be significant in job hiring, promotions, career progression and pay, and may be institutionalised rather than overtly discriminatory (Raghavan *et al.*, 2020).

CBT will, therefore, be employed as an interpretative theory in this study and not as a measured variable. The study does not infer that the wage gap or lack of participation is evidence of cognitive bias. Rather, cognitive bias is used to explain the lack of workforce participation, leadership representation, and compensation outcomes when organisations seem to be out of balance, despite the all-pervasive nature of AI-powered systems. The theoretical lens then allows consideration of how inclusive workforce development is achieved amid technological change, and of the role of embedded and existing organisational asymmetries in sustainable skills development in Industry 4.0 contexts.

LITERATURE REVIEW

Sustainable Skills Development in Industry 4.0

Industry 4.0 has revolutionised the way organisations build and maintain competitive advantage. In addition to the traditional role of employment, access to new technological opportunities is becoming more crucial than ever for workforce sustainability (Sony and Naik, 2020). Sustainable skills development is therefore not just about training and capability building, but also about being involved in AI-related roles, being part of future-oriented career pathways and technologically resilient workforce systems.

However, the shift towards Industry 4.0 has created a new paradox. Although digital transformation is projected to create more opportunities and increase productivity in the workforce, research indicates that access to new technological ecosystems is not evenly distributed (Antony *et al.*, 2023). Saniuk *et al.* (2023), in their research on the required skills for managerial staff in Industry 4.0, found that while 68% of the staff were open to changes in digital transformation, only 41% were ready to implement the actual innovation. This difference points to the gap in skill development in the first place. Moreover, Zhou *et al.* (2024) showed that AI leads to unequal access opportunities for employees when organisational accountability and responsibility are lacking. In addition, increased engagement in technical and AI-dependent industries is defining the path to acquiring future-relevant skills while leaving others behind to



face technological displacement. In this context, the discussion changes from whether organisations are embracing technology to whether the opportunities afforded by technological change are equitably shared across workforce groups. Therefore, a sustainable challenge for skills development may be less about developing future skills and more about access to the pathways through which these skills are developed and applied within the organisation.

AI-Enabled Workforce Systems and Organisational Transformation

AI is widely recognised as a tool to increase efficiency and fairness within workforce systems by helping to objectively assess and reduce reliance on human judgements (Tambe *et al.*, 2019). These assumptions have paved the way for AI to become a means to solve age-old organisational challenges in workforce management and human decision-making. But there's an interesting paradox in organisations as AI use grows.

In a study by Karunakaran *et al.* (2025), it was found that more than 80% employers report using automated hiring systems using AI; however, concerns about biases threaten to exacerbate inequality in regulatory responses. As AI increases objectivity and decreases human subjectivity, the differences in the workforce should gradually shrink. However, as more AI-driven workplaces emerge, the evidence continues to show that there are persistent disparities in participation, promotion, and workplace valuations. This raises the question as to whether technological change alone is able to yield equitable organisational outcomes.

However, emerging research indicates that the progress of technological optimisation and organisational inclusion are not always linked. Although AI can enhance operational results, algorithmic systems typically operate in organisational settings that have been influenced by past organisational structures, institutional norms, and decision-making practices (Chen, 2023). Consequently, there are potential benefits to productivity as well as ongoing inequalities in organisational structures, progression and recognition (Sony *et al.*, 2025; Tortorella *et al.*, 2020). This poses a crucial contradiction in Industry 4.0 workforce systems. Moreover, the impact of AI from a sustainability standpoint should be evaluated as much on productivity as on its ability to facilitate a fairer workforce, the structure of opportunities and long-term organisational resilience. This changes the focus from technology adoption to the organisational results that can be achieved with workforce systems powered by AI.

Cognitive Bias and Organisational Evaluation

Increasingly, organisational research has indicated that workforce inequalities begin to develop as a result of cumulative evaluation processes, not as direct discriminatory actions. Leslie *et al.* (2017) suggest that inequalities in employment outcomes can occur at the level of organisational systems that shape opportunity allocation, performance recognition, promotion systems and leadership development. A UNESCO (2021) report found that women constitute only 22% of the AI workforce, indicating underrepresentation. The results indicate that inequities can exist despite sharing the same values, fairness and inclusion.

Bias can be experienced at the individual level, but it can also be influenced by organisational norms and practices that affect career trajectory, representation in the workforce and opportunity for promotion. This takes special significance in an AI-driven setting. Studies have shown that algorithmic systems can perpetuate the existing organisational asymmetries as historical patterns of employment are fed into the data and evaluation systems (Köchling and Wehner, 2020; Chen, 2023). Importantly, that does not mean inequity necessarily indicates discrimination, as stated in the CBT. Instead, it offers a lens for understanding scenarios where workforce participation, representation in leadership and earnings disparities persist despite workforce contributions. Taken together, these studies suggest that organisational structures, leadership representation, and compensation may be influenced by more general organisational evaluation structures than by objective measures of performance.

Workforce Inclusion and Organisational Sustainability

In recent years, there has been a growing body of research that places the issue of workforce inclusion in a strategic organisation's capacity, which drives innovation, resilience and long-term adaptability (Aust *et al.*, 2020). Not leveraging available talent can undermine leadership pipelines, limit knowledge diversity and diminish the ability to adapt to technological disruption within an organisation. Sustainable organisational development in Industry 4.0, therefore, not only relies on technological progress but also on the ability of workforce systems to allow equitable participation and progress in the workplace, as well as the development of a workforce valuation system. In this light, workforce inclusion is a prerequisite for sustainable skills development as access to emerging opportunities determines which people will be included in the future workforce and who will not be included.

Collectively, the literature suggests that the challenge facing Industry 4.0 is no longer whether AI can create opportunities, but whether organisational systems distribute those opportunities equitably across workforce groups.

Research Gap

Industry 4.0 literature largely assumes that technological transformation creates new opportunities for workforce development through AI, automation, and digital innovation. However, considerably less attention has been given to whether organisational systems distribute these opportunities equitably. Current studies focus on either AI adoption, employee competence development, or algorithmic bias alone, while few studies include the impact of AI participation, leadership growth, and recognition on future AI-related skills and opportunities in the workplace. This gap is significant because it depends not just on access to opportunities for skills development within an organisation, but also on who might access, develop, and benefit from such an opportunity in an AI-powered environment.

RESEARCH METHODS

Research Design

This study uses an exploratory secondary data research design to examine the relationship between AI, human cognitive biases, workforce inclusion, and sustainable skills development in the context of Industry 4.0. The research uses publicly available secondary datasets to analyse how AI-driven organisational systems influence workforce participation, leadership inclusion, productivity, and sustainability outcomes across gender groups.

The UNESCO (2021) is used to examine macro-level workforce inequalities associated with digital transformation, including women's participation in AI-related professions, leadership representation, automation vulnerability, and structural workforce exclusion. In addition, the Kaggle (2026) dataset titled “AI Impact on Job Sector” is used to explore micro-level organisational outcomes associated with AI adoption, including productivity improvement, salary changes, and workforce performance patterns across industries.

Asymmetries may be measured indirectly through indicators of workforce participation, leadership representation and productivity–reward outcomes in the study, as these are not directly observable in secondary datasets. These indicators are not direct measures of bias, but they provide evidence of actions that might result

from cognitive bias in the organisation. The study combines the interpretation of the UNESCO (2021) report with secondary data analysis of the Kaggle (2026) dataset, which is an exploratory organisational simulation dataset, to gain a comprehensive view of the interconnection between workforces driven by AI and the inclusion and sustainability of organisations. The UNESCO (2021) report is chosen because it contains internationally recognised evidence in the areas of gender inclusion, digital economy, Industry 4.0 sustainability challenges and workforce transformation. The Kaggle dataset extends this by providing simulated organisational-level workforce indicators related to AI integration.

Data Analysis

The Kaggle dataset was analysed using Microsoft Excel pivot tables and percentage-based comparison techniques to examine workforce performance outcomes associated with AI adoption across gender categories and sectors.

The percentage change in salary was calculated using the following formula:

$$\text{Increment in Salary \%} = [(\text{Salary after AI} - \text{Salary before AI}) / \text{salary before AI}] * 100$$

The quantitative analysis focused on three variables:

- Gender
- Salary Percentage Change after AI adoption
- Employee Performance Improvement

Following this, comparisons were drawn across gender groups and sectors to assess whether equitable compensation was offered post-AI implementation in organisations. This comparison examined how inclusive workforce systems may strengthen organisational resilience, sustainable workforce planning for skill development, and AI-enabled human resource management practices.

ETHICAL STATEMENT

Secondary data have been used in the study and are available from publicly available sources (UNESCO, 2021; Kaggle, 2026). The researcher did not secure personal interviews, private employee information, or confidential organisational records during the research. This study, therefore, does not pose any ethical concerns regarding the privacy or confidentiality of participants. To maintain research integrity, all secondary sources were appropriately acknowledged and interpreted within the limitations of exploratory organisational sustainability analysis.

RESULTS AND ANALYSIS

Workforce Participation Asymmetry and Automation Vulnerability in Industry 4.0 (RQ1)

Using data from UNESCO (2021), workforce participation, inequalities and automation vulnerability were examined for the analysis around four workforce indicators: women researchers globally, AI professionals globally, employment in high automation-risk occupations, and employment in low automation-risk occupations, as shown in Table 1. The extracted data were organised in Microsoft Excel and analysed using comparative percentage analysis to identify workforce participation asymmetries between men and women within AI-oriented economic systems and identify structural workforce patterns associated with digital transformation and sustainable workforce participation.

Table 1: UNESCO Workforce Participation and Automation Vulnerability Analysis

Indicator	Women %	Men %
Women researchers globally	33.3	66.7
AI professionals globally	22	78
High automation-risk jobs	70	30
Low automation-risk jobs	43	57

Source: Data compiled by authors using UNESCO (2021) - <https://unesdoc.unesco.org/ark:/48223/pf0000377456/PDF/377456eng.pdf.multi.page=1&zoom=auto,-16,842>

Table 1 shows a substantial decline in women’s participation in global research systems and their representation in AI-oriented professions. Although women account for 33.3% of researchers globally, participation decreases to 22% within AI professions. Despite growing digital transformation, women remain underrepresented in AI-oriented occupations while being disproportionately concentrated in high automation-risk roles. The pattern indicates a structural participation asymmetry in Industry 4.0 workforce systems regarding access to technologically resilient occupations.

From a sustainability perspective, this asymmetry could potentially place a strain on organisational resilience by limiting the diversity of future talent pipelines as well as adaptive capacity against changing AI-driven environments. While the study does not directly assess the level of bias, the consistent lack of women in higher-impact AI roles is reflective of the core premise of the CBT, which indicates that organisational practices and awareness of technical expertise and leadership readiness may persist.

This implies, however, that the findings contradict the notion that technological development is a causal factor in workforce equality. Rather, they argue that even in the digital world, specific inequalities within organisations could re-emerge if they are not addressed with inclusive governance of the workforce and equitable distribution of new technical possibilities.

Technical Inclusion and Leadership Ecosystems in AI-Oriented Organisations (RQ1)

The second phase of the analysis compared the contribution of women in technical roles with the representation of women in leadership roles in selected multinational technology organisations. The analysis centred on Apple, Google, Microsoft, Facebook, and Samsung, seeking to understand whether technical inclusion and leadership representation are interconnected patterns of organisational diversity, or whether they are simply individual dimensions of diversity outcomes.

Table 2: AI Inclusion and Leadership Correlation

Company	Women Technical Roles %	Women Leadership %
Apple	23	29
Google	21	24
Microsoft	20	20
Facebook	23	33
Samsung	17	6

Source: Data compiled by authors using UNESCO (2021) - <https://unesdoc.unesco.org/ark:/48223/pf0000377456/PDF/377456eng.pdf.multi.page=1&zoom=auto,-16.842>

Table 2 indicates that higher levels of women’s participation in technical roles are generally accompanied by stronger representation in leadership positions. While the limited sample size restricts statistical generalisation, the pattern suggests that technical inclusion and leadership inclusion may operate as interconnected organisational conditions rather than independent diversity outcomes.

Organisations with higher female participation in tech roles tend to have greater female leadership representation, whereas organisations with low technical participation tend to have less representation in leadership. This pattern suggests that the barriers may not be surface-level, but are deeply ingrained throughout recruitment, promotion and leadership advancement. Within the scope of CBT, these tendencies could represent organisational evaluation processes that affect access to opportunity

and promotion over time. Asymmetries can be added across the workforce systems, affecting participation in technical jobs and advancement into higher positions.

The findings suggest that workforce inclusion is not just an outcome of HR configuration but a strategic organisational capability. Organisations that successfully incorporate women into technical positions may have improved opportunities for multi-generational leadership paths and enhanced innovation and future adaptability. However, the absence of technical involvement may inhibit further advancement into leadership positions and workforce readiness for Industry 4.0.

The findings reveal a strong correlation between all industries and AI usage and productivity improvements, for both men and women. However, the link between increases in productivity and compensation outcomes is not consistent across gender groups.

Comparative Analysis of Salary Increment and Productivity Improvement After AI Adoption

This analysis focused on the percentage increase in salaries following the introduction of AI and the improvement in staff productivity (Kaggle, 2026).

Table 3: Comparative Analysis of Salary Increment and Productivity Improvement After AI Adoption

Sector	Female Salary Increment	Male Salary Increment	Female Productivity Improvement	Male Productivity Improvement
Education	5.75%	6.46%	12.13%	8.83%
Finance	5.86%	5.84%	9.43%	9.18%
Healthcare	5.70%	8.80%	9.33%	10.36%
IT	5.83%	6.17%	10.68%	8.21%
Manufacturing	4.89%	5.66%	12.54%	9.60%
Marketing	5.12%	7.08%	11.53%	11.30%
Retail	6.01%	7.35%	7.71%	8.86%
Average	5.60%	6.75%	10.50%	9.49%

Source: Data compiled by authors using Kaggle (2026) - <https://www.kaggle.com/datasets/sumeakash/ai-impact-on-job-sector>

The sectoral analysis in Table 3 indicates that AI adoption is associated with productivity improvements across all industries for both men and women. However, the relationship between productivity gains and compensation outcomes is not consistently aligned across gender groups.

Females had higher productivity improvements on average (10.50%) than males (9.49%), but lower average salary growth (5.60% compared with 6.75%). This tends to occur at the same speed and to the same extent across the IT, Education, and Manufacturing sectors, with women demonstrating higher productivity at lower wages. The results indicate a possible productivity mismatch in AI-assisted work organisation systems.

Importantly, the results do not confirm individual managerial bias or discriminatory intent. Instead, they argue that the cost of compensation may not be a direct function of measurable improvement in performance. The gap between productivity contribution and salary growth may suggest the impact of wider organisational valuation structures that remain influential workforce recognition and reward.

The observed pattern is consistent with the CBT argument that organisational decisions can be determined by existing beliefs and assumptions, as well as by their performance measures. While AI might improve functioning, the research indicates that the use of technology does not guarantee fair employee results.

From a sustainability point of view, this may lead to low trust, retention, engagement, and future employee development, as well as undermine skill development. Thus, the decision to use AI and its impact on sustainability measures will be closely tied to productivity benefits and to organisations' capacity to integrate salaries, rewards, and promotions with transparently tracked labour governance methods.

Integrated Organisational Sustainability Interpretation (RQ2)

The UNESCO (2021) findings indicate that women remain underrepresented in AI-intensive occupations and leadership pathways, while the Kaggle analysis demonstrates that productivity improvements do not consistently translate into equivalent compensation outcomes. Viewed together, these patterns suggest that technological advancement alone may be insufficient to eliminate existing organisational inequalities.

AI does not seem to act as a corrective mechanism, but rather a power player that fits into existing organisational frameworks and labour processes. In this way, the capacity of AI to facilitate sustainable skills development is closely tied to the governance mechanisms for technology implementation and management. The results also indicate that a complex interplay between technical inclusion, leadership participation, workforce recognition, and access to advancement opportunities influences the sustainability of the workforce. When they are not evenly distributed,



organisations will inadvertently leave behind a form of developmental imbalance whereby technological development is outpaced by workforce inclusion.

The findings are consistent with the proposition that cognitive bias may operate through organisational structures even as decisions become more data-driven. Overall, the results indicate that, when informed by productive and sustainable recognition and reward systems, AI systems can play a positive role in workforce productivity, but when those gains are not distributed to workers fairly, they are not enough to support inclusive and sustainable organisational development.

DISCUSSION

Results show that technological and workforce transitions may not take place simultaneously. Despite the progress achieved by AI-powered systems, there is still a lack of equality in workforce engagement, leadership representation, and reward outcomes. Therefore, technological opportunities are available for development in line with Industry 4.0. However, only through recognition, opportunities, and sustainable skill development can Industry 5.0 be fostered to achieve organisational resilience. From a CBT perspective, these imbalances might result from internal organisational evaluation systems that continue to influence workforce outcomes even as processes become increasingly AI-driven. To address this imbalance, a synergistic approach between AI and human intelligence (Industry 4.0 and Industry 5.0) is required for long-term organisational sustainability.

RECOMMENDATIONS

With Industry 4.0 shifting to Industry 5.0, it is important to continually evaluate and monitor gaps in participation, promotion, leadership representation, and compensation in workforce planning to address potential asymmetries in AI-driven systems. Organisations should implement:

- Clear structured pathways that connect workforce contributions to AI-intensive roles,
- skills acquisition through development metrics like AI-related capability development, leadership readiness, and increased participation in digital learning, and
- transparent promotion and reward systems to ensure that employee productivity bene-fits from AI governance frameworks.

LIMITATIONS

This study is exploratory and relies on secondary datasets and a small sample size that do not directly measure cognitive bias, organisational culture, or individual decision-making processes. Consequently, CBT is employed as an interpretive approach rather than a causal explanation. The study also focuses on workforce participation, leadership representation, and productivity-reward outcomes as proxy indicators of sustainable skills development. Future studies should confirm these results in primary organisational investigations, a longitudinal workforce analysis and industry-specific investigations that can explore changes in participation, career progression and recognition over time. Additionally, there is a need to further investigate the potential impact of AI-driven systems on both the amplification and transformation of organisational asymmetries in various sectors, organisational scales, and national contexts.

CONCLUSIONS

This research shows that technological and workforce transformations do not always follow each other in an Industry 4.0 setting. The use of AI brings organisational efficiency and productivity, but gaps in workforce participation, leadership roles and reward are still evident. The results indicate that not only are there challenges in skills development capability creation, but that there is a need for equal opportunities to participate, promote and reward skills within organisations. In Industry 5.0, sustainable AI-powered organisations will be judged not only on technological advancements, but also on inclusive workforce governance.

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BIOGRAPHY



Nikolija Micunovic Mester is a DBA scholar at Rushford Business School, Switzerland, and an accomplished Human Resources Director at AMAN, a global luxury hospitality brand. With over ten years of experience in human resources, leadership coaching, employee development, and organisational culture, she has built her career around creating people-centred workplaces that support both employee well-being and business excellence. She holds an MBA from the University of Wales, Cardiff, and is a Professional Certified Coach through the Centre for Coaching Certification. Her research and professional interests focus on HR excellence, burnout prevention, sustainable leadership, and employee well-being in the luxury hospitality sector.



Prof. Anuj Kumar is a Professor and Global Country Head at Rushford Business School, Switzerland, where he also leads the Research and Doctor of Business Administration (DBA) programme. He is a Post-Doctoral Fellow in Malaysia and holds a dual PhD from Aligarh Muslim University (India) and the All-India Management Association, New Delhi. He is also the Editorial Head at Confab 360 Degree, India's first IAF-ISO certified organisation. Dr Kumar has established research and academic collaborations with institutions across the globe. He has authored more than 100 research papers in Scopus-indexed journals, with an h-index of 13 and nearly 500 citations.